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Letter to the Editor

An analysis of wind power density derived from several wind speed density functions: The regional assessment on wind power in Malaysia

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ABSTRACT

In wind turbine design and site planning, the probability distribution of wind speed becomes critically important in estimating energy production. The utilization of accurate distribution will minimize the uncertainty in wind resource estimates, and consequently, it will improve the result in the site assessment phase of planning. In general, different region will have different wind regime. Hence, it is reasonable that different wind speed distribution will be found for different region. In this study, the features of wind power density based on the dependency of the suitable wind speed density have been obtained analytically using transformation technique. Since the wind power density has been obtained, the mean power density which is referred as an important indices related to the estimation of potential wind energy have been obtained by using the concept of raw moment and Monte Carlo approach. An analysis of semivariogram indicates the lack of spatial correlation of the wind power in Malaysia. The map of the mean power density over Malaysia indicates that several regions such as northeast, northwest and southeast region of Peninsular Malaysia and southern region of Sabah are found as the best region to be further investigated in the future for the wind energy development.

1. Introduction

Various studies on wind speed have been carried out by many researcher, particularly for the purpose of generating energy [1–3]. The growing interest in wind as a possible source of energy for producing electricity nowadays is dated to the oil crisis that occurred in the mid-seventies [4]. Wind energy has become an important alternative renewable source of energy because it is clean and cost effective for many applications such as electric power production, water pumping, etc. The utilization of wind as an energy resource has been growing rapidly worldwide because the consumption of other energy resources such as oil-, nuclear-, and coal-based resources contribute to environmental pollution and global warming. Therefore, wind energy has been considered as a green technology due to its minor impact on the environment, with the significance increasing of environmental problems, clean energy generation becomes essential in every aspect of energy consumption. Wind energy does not impose a transportation problem and its utilization does not require advanced technology [5,6].

The distribution of wind speeds predominantly determines the performance of wind energy system in a given location and time [7]. Information about the wind speed probability density function (pdf) is very important for selection of wind farms, assessment of wind energy potential, design of wind farm, power generator and operation management of wind power conversion system [8,9]. Morgan et al. [10] stated that the probability distribution of wind speed is critically important in estimating energy production for wind turbine design and site planning. It has been defined in engineering practice, the average wind turbine power, $\overline{P}_w$ associated with the probability density function of wind speeds X is obtained from

$$\hat{\overline{P}}_w = \int_0^\infty P_w(X) f(X) dX \tag{1}$$

where $f(X)$ is the pdf of X and $P_w(X)$ is the turbine power curve that used to describe the power output from the wind speed. Morgan et al. [10] also stated that the largest uncertainty in estimation of $\overline{P}_w$ lies in the choice of wind speed pdf, $f(X)$, since the turbine manufacturer knows $P_w(X)$ fairy accurate. Thus, the utilization of more accurate wind speed pdf will minimizing the uncertainty in wind resource estimates, and consequently, it will improve the result in the site assessment phase of planning.

On the other hand, once suitable distribution of wind speed has been known, wind power distribution can also be derived to get better information about the wind power as well as the energy production. In most studies, the assessment on the wind power density has been derived from Rayleigh or Weibull distribution (for example see, [11–13]). However, several authors have indicated that the Weibull and Rayleigh distribution should not be used in a generalized way, as they unable to represent some wind regimes (for example, see [10,14,15]). Thus, in order to minimize the uncertainty in wind resource estimates, the wind power density should be derived from the most suitable form of wind speed pdf. Here, we focus on derivation and the analysis of wind power distribution obtained from various wind speed pdf in Malaysia.

2. Some reviews on wind energy potential in Malaysia

The worldwide capacity of wind energy has been reached up to 159,213 MW, where Asia has been accounted as the largest shared of new installations of wind turbine, which is up to

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40.4%, followed by North America, 28.4% and Europe by 27.3%. Based on development of wind energy all over the world, WWEA was expect that global capacity of wind energy can be reach up to 1,900,000 MW by 2020 [16]. In Malaysia, it is suggested that the potential for wind energy generation depends on the availability of the wind resource which is found to vary according to location [4]. Among the early works on wind energy research in Malaysia is the work by Sopian et al. [17]. They have analyzed 10 wind stations in Malaysia using Weibull distribution. Their results indicate that Mersing and Kuala Terengganu possess the best potential for wind energy development. In addition, their analysis also indicates that the application involving small wind turbines could be used to provide electricity on the relatively undeveloped East coast of peninsular Malaysia and offshore islands which are not connected to the national grid. Furthermore, Chiang et al. [18] mentioned that the annual offshore wind speed in Malaysia is around 1.2–4.1 m/s with the highest potential is in the east Peninsular Malaysia with annual vector resultant wind speed of 4.1 m/s. Apart from that, most recent research on evaluation of wind energy potential Malaysia is by Islam et al. [19]. They have analyzed the wind energy potential at Kudat and Labuan by using 2-parameter Weibull distribution. Their results conclude that small-scale wind energy can be generated at the turbine height of 100 m. In addition, Masseran et al. [20] has been evaluated the characteristic of wind speed and the potential of wind energy for 10 wind stations in peninsular Malaysia based on the persistence concept. They indicate that the stability of wind speed in peninsular Malaysia is quite good. However, in term of energy production, the persistence level at a 4 m/s truncated level are found to be not enough to ensure the sustainable energy production.

The energy efficiency and renewable energy under the Eight Malaysian Plan (2001–2005) and Ninth Malaysia Plan (2006–2010) also mentioned on targeting the renewable energy to be significant contributor for better utilization of energy resources. In addition, an emphasis to further reduce the dependency on petroleum provides the more effort to integrate alternative source of energy. Thus, awareness on the potential of the harvesting the wind energy Malaysia, various institutions of higher learning and research institutions like UKM and UTM have conducted an active research and development in the field of wind energy. It has been described by Ong et al. [4], 150 kW wind turbine which was built in Terumbu Layang–Layang in 2005 had demonstrated some success. In 2007, Malaysian Government under joint venture partnership with the State Government of Terengganu and Tenaga Nasional Berhad (TNB), which is the only electricity supplier in Malaysia is embarked on the project of integrating power supply at Pulau Perhentian. The project consists of installing two wind turbine, solar farm (Solar Panel), Generator and battery. On the other hand, the Ministry of Rural and Regional Development had built 8 small units of wind turbine in Sabah and Sarawak for local communities [4]. Ong et al. [4] also reported that a tourist resort island in Malaysia is found to having a great potential for wind energy conversion system. In addition, Shafie et al. [21] described that a northwestcoast of Sabah and Sarawak region is having a potential to generate wind energy due the wind strength that can be reach 20 knot or more. However, based on our observations, we conclude that the researchs on the wind energy in Malaysia are not windespread. Thus, more in depth studies have to be carried out in Malaysia in order to explore this oppurtunity.

3. Some reviews on related studies for wind energy spatial mapping

The complete sampling of the wind data at a particular surface is impossible, thus predicting the wind power at unobserved location is importance in order to get some understanding about the behavior and characteristics of the wind regime as well as the power potential at a particular surface. In addition, since wind power varies according to sites, it is reasonable to consider that there exist spatial characteristics between the locations considered in the study. Observations in close spatial proximity are expected to be more similar than observations that are more spatially separated. Saidur et al. [22] have been mentioned that the first requirement on wind energy is the assessment of the nationwide wind energy potential. Thus, for efficient exploration of the wind energy potential, a nationwide assessment based on the wind power map is required. There are various approach and tools that are found to use by several researchers for the purpose of modeling and spatial prediction on wind energy potential such as statistical and geostatistical analysis, artificial neural network, geographic information system (GIS), etc. In this study, we focus on statistical ang geostatistical analysis in order to provide a maps of wind power distribution in Malaysia.

Cellura et al. [23], for example, use inverse distance weighting and universal kriging methods for spatial prediction of wind speed in Sicily. They found that their wind speed map are quite similar to the Italian Wind Atlas. Shoji [24] have analyzed the wind speed data for mountainainous Chubu and plain Kanto district in Japan by using the statistical and geostatistical approach. The method of fiiting distribution and spatial variogram has been used to describe the characteristics of wind regime as well as the wind power generation in Japan. Zlatev et al. [25] have provided the interpolation maps for in-situ wind sensor data in an area for approximately 200 km by using the geostatistical interpolator known as a kriging. They found that a kriging is simple but effective solution for estimating the wind variables. Apart from that, Luo et al. [26] have used the methods of semivariogram and cokriging for estimating the wind speed surface across the United Kindom. Thier results indicate that cokriging method can produce a good estimation of continous surface for wind speed. On the other hand, Rozsavolgyi [27] used a geostatistical model known as Complex Multifactoral Polygenetic Adaptive Model (CMPAM) to provide a wind speed map in order to describe the Hungarian wind condition. Alsamamra et al. [28] provided a 1-km spatial resolution surface wind speed map for Andalusia, Southern Spain by using a residual kriging. Their results found that a map of wind speed produced by a residual kriging give a good estimates on particularly for region with high and low wind speed estimates. In addition, Glinou et al. [29] used the multivariate ARFIMA model accompanied with the kriging method to predicting a wind potential at a Crete, Grece. Their result indicates the reasonableness of multivariate ARFIMA and kriging method in predicting the spatial wind speed for unobserved location.

Since the spatial mapping of wind data is important for wind energy planning purpose, this study try provides a rough map of wind power by using the statistical and geostatistical analysis to identify which region in Malaysia has the potential of generating wind energy before a more in depth analysis is carried at the specific area. Fig. 1 shows a the process of this research work.

4. Study area and data

Malaysia is a country which lies entirely in the equatorial zone, situated in the south east part of Asia, having a geographic coordinate of 2°30′ in the north latitude and 112°30′ in the east longitude. Throughout the year, Malaysia experiences a wet and humid condition with daily temperature ranging from 25.5 to 35 °C. The wind that blows across the peninsula as well as Sabah and Sarawak is influenced by the monsoon seasons, namely

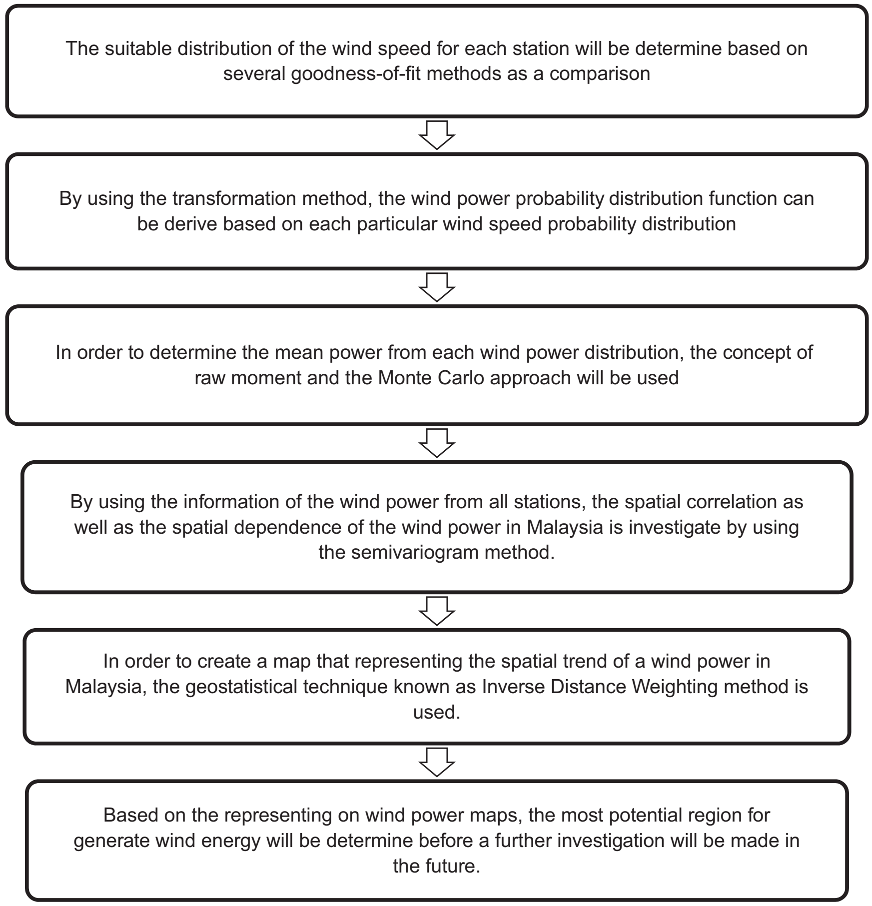

Fig. 1. Flow chart of the research activities.

southwest monsoon, northeast monsoon and two short inter-monsoons. The two monsoons that contribute to rainy seasons are the southwest monsoon, occurring in May until September, and the northeast monsoon which occurs from November until March. The later monsoon brings about heavier rainfall in the peninsula, with the worst affected areas are in the east and south. Malaysia is a maritime country which is also influenced by the effect of sea breezes and land breezes especially when the sky is not cloudy. During most afternoons, sea breezes occur with speeds of 10–15 knots. However, at night, the reverse process occurs. Weak land breezes occur in coastal areas.

The data used in this study which consists of hourly wind speed (km/h) from January 2000 to November 2009 for 67 wind stations across the country was obtained from the Department of Environment and Malaysian Meteorology Department.

5. Methods

5.1. Wind power formulation

The wind power is defined as a proportional to the cube of wind speed, X, provided the air density, ρ is a constant. The power transported by an airstream flowing with a given speed X can be calculate as

$$P = \frac{1}{2}A\rho X^3 \tag{2}$$

where A is the area of the airstream measured in a perpendicular plane to the direction of wind speed [7,12]. However, the conversion factor and loses are not considered in this formula. Thus, it is interpreted as a power transported by the wind. In order to calculate the power that can be extracted by the rotor of wind turbine, Betz' law need to be taken into account [11]. Betz' law stated that, no wind turbine can capture more than 59.3% of kinetic energy in wind. In fact, the modern wind turbine technology also can not operate beyond the Betz limit. On the other hand, it states that a maximum portion of the power transported by the wind that can be converted into mechanical power by such converter is about 16/27. Thus, by considering Betz' law, Eq. (2) can be written as

$$P_B = \frac{8}{27}A\rho X^3 \tag{3}$$

However, in a more realistic case involving a wind turbine, the power coefficient is found better than Betz' law in evaluate the power produce. The power coefficient C_p is the ratio between the power produced by a wind turbine and the power carried by a free airstream. The range of power coefficient, C_p is between 0 and the Betz limit. Thus, the power can be extracted from airstream by considering a power coefficient C_p can be written as

$$P_{C_p} = \frac{1}{2}A\rho X^3 C_p(\lambda,\beta) \tag{4}$$

The wind speeds, X from Eqs. (2)–(4) may vary during the period of time. To consider this effect, the information about the wind speed pdf need to be included in the calculation of wind power [11], as mention in Eq. (1).

5.2. Transformation method

In order to obtain wind power distribution, a change of variable technique may be operated. Transformation method is

one of the technique that usually being used to finding the probability distribution functions of a random variables. The distribution of random variable $P=h(X)$, where the variable P is a function of random variable X, provided $h(x)$ is a monotonic function, that is either increasing or decreasing function, and X has a probability distribution function $f_X(x)$. Then, by using transformation method, the distribution of P can derived as

$$f_P(p)=f_X(h^{-1}(p))\left|\frac{d[h^{-1}(p)]}{dp}\right| \tag{5}$$

where h^{-1} denotes the inverse function [11,30]. In this study, the distribution of $P=\frac{1}{2}A\rho X^3$, $P_B=\frac{8}{27}A\rho X^3$ or $P_{C_p}=\frac{1}{2}A\rho X^3 C_p(\lambda,\beta)$ will be derive depending on the selected case. Let $u=\frac{1}{2}A\rho$, $u=\frac{8}{27}A\rho$ or $u=A\rho C_p(\lambda,\beta)/2$. To make it simpler, let $A=1$ indicating the wind power per unit area. The function of interest here is $p=ux^3$ which is increasing for $x>0$. Thus, $h^{-1}(p)=(p/u)^{1/3}$ with $d[h^{-1}(P)]/dp=1/3u^{1/3}p^{2/3}$.

5.3. Spatial correlation and spatial estimation

Since wind power may vary according to locations, it is reasonable to investigate the spatial correlation between the location considered in the study. Here, the spatial correlation of wind power is investigated by using the semivarigram plot. After that, in order to gain some insight on the wind power variability in Malaysia the inverse distance weighting method is applied.

5.3.1. Semivariogram

Semivariogram is a tool which is often used to investigate spatial correlation as well as the spatial dependence of the data before spatial prediction is done. Let $Z(s_i)$denote the mean speed for the ith station given a particular choice of the wind speed distribution. Semivariogram reconstruct the properties of auto-covariance for the spatial process in d dimension denoted as$\{Z(\mathbf{s}):\mathbf{s}\in\Re^d\}$, where $\boldsymbol{s}$ is the location at which attribute Z is observed. Semivariogram is define as

$$\begin{aligned}\gamma^*(\mathbf{s}_i,\mathbf{s}_j)&=\frac{1}{2}Var\left[Z(\mathbf{s}_i)-Z(\mathbf{s}_j)\right]\\&=\frac{1}{2}\left\{Var[Z(\mathbf{s}_i)]+Var[Z(\mathbf{s}_i)]-2Cov[Z(\mathbf{s}_i),Z(\mathbf{s}_i)]\right\}\end{aligned} \tag{6}$$

Semivariogram function that depends upon separation vector only through its length $\|\mathbf{s}_i-\mathbf{s}_j\|$ is called isotropic; if not, it is anisotropic. A valid semivariogram function can also be constructed from a valid covariance function, where a valid covariance function is a positive-definite function, such that $\sum_{i=1}^k\sum_{j=1}^k a_i a_j C(\mathbf{s}_i-\mathbf{s}_i)\geq 0$ for any set of real number $a_1,\ldots,a_k$. Parametric forms that are available as candidates for semivariogram are linear, spherical, exponential, wave, rational quadratic, etc (see, Appendix A). The candidate model is chosen based on the "closeness" between the theoretical semivariogram and the empirical semivariogram which is calculated by

$$\hat{\gamma}(\mathbf{h})=\frac{1}{2N(\mathbf{h})}\sum_{(\mathbf{s}_i,\mathbf{s}_j)\in N(\mathbf{h})}[Z(\mathbf{s}_i)-Z(\mathbf{s}_j)]^2 \tag{7}$$

where $\mathbf{h}=\|\mathbf{s}_i-\mathbf{s}_j\|$ is a distance between locations $\boldsymbol{s}_i$and $\boldsymbol{s}_j$ and $N(\boldsymbol{h})$ denotes the set of pairs of locations at distance $\boldsymbol{h}$ [31]. In this study, this measure of "closeness" may be based on mean square error.

5.3.2. Inverse distance weighting method (IDW)

Complete sampling of the random field surface is impossible, thus predicting the random field at unobserved location is importance for spatial data. Various method of is available in spatial statistic to make prediction, estimation or interpolation for random field such as Inverse Distance Weighting Method, Kriging, Nearest Neighbor, Minimum Curvature, etc. In this study, Inverse Distance Weighting Method will be used in order to get some overview about spatial estimation of wind power in Malaysia. IDW is the method for spatial estimation of random field. It was a weighted average interpolator, and can be either an exact or a smoothing interpolator. In IDW, data has been weighted during interpolation such that the influence of one point relative to another decline with a distance. The value of $p(\boldsymbol{Z};s_0)$ at the location s_0 can be estimated by using a weighted mean of the available measurement through the expression

$$p(\mathbf{Z};s_0)=\frac{\sum_{i=1}^n W(s_i,s_0)Z(s_i)}{\sum_{i=1}^n W(s_i,s_0)} \tag{8}$$

where $Z(s_i)$ is the observed data for n sites, (s_i,s_0) is the distance between i-th measurement station with the s_0 location. $W(s_i,s_0)$ is the weighting factor which is a decreasing in term of distance. Its value decreases with the distance following a quadratic or exponential law [23].

6. Result and discussion

In order to describe the behavior of wind speed at a particular location, it is necessary to identify the distribution which best fits the data. Suitable distributions for each wind station has been determined by fitting nine types of statistical distribution to the data, namely Weibull (WE), Burr (BR), Gamma (GA), Inverse Gamma (IGA), Inverse Gaussian (IGU), Exponential (EX), Rayleigh (RY), Lognormal (LN) and Erlang (ER) to the data. Here, ER is just a special case of Gamma distribution where the shape parameter is an integer. In this study, parameter estimation for each model is done by using maximum likelihood method. Table 1 below shows the list of probability density functions with their respective maximum likelihood estimator, for details see [10,15,32,33]. The maximum likelihood estimator (MLE) for the parameters of WE, GA, IGU, ER, IGA, BR distributions can be determined numerically by using methods such as Newton-Rapson, scoring, EM algorithm, quasi-Newton, Nelder–Mead method etc. In this study, Nelder–Mead method was used as an optimization technique for determining the MLE of the parameters [34]. For other distribution such as LN, RY, and EX the MLEs can be easily determined. Results on parameter estimation for each model are show in Appendix B.

Several goodness of fit tests which include Kolmogorov–Smirnov (KS), Akaike's Information Criterion (AIC) and Bayesian Information Criterion (BIC) are used to determine the most suitable statistical distribution for the data of each wind station. In addition, R^2 coefficient was also used to evaluate the goodness of fit for each method. A large value of R^2 indicates a better fitted theoretical distribution to the data. Table 2 shows a list of most suitable statistical distribution for each wind station.

It was found that only 5 types of statistical distribution that is Gamma, Burr, Weibull, Erlang and Inverse Gamma have been selected as the most appropriate distribution for each station which varies according to the location of the stations.

6.1. Wind power density derived from suitable wind speed density

6.1.1. Wind power density derived from Weibull (WE)

We were among most widely accepted distribution for wind speed [10]. It is also have a relationship with other distribution such as Exponential, Erlang, Truncated Rayleigh and Standard Extreme Value distribution for some particular value of shape and

Table 1
List of probability density functions and maximum likelihood estimators.

Model	Probability density function (PDF)	Maximum likelihood estimator (MLE)
LN	$f(x)=\frac{1}{x\sigma\sqrt{2\pi}}\exp\left[\frac{-(\ln(x)-\mu)^2}{2\sigma^2}\right]$	$\hat{\mu}=\frac{\sum_{i=1}^{n}\ln x_i}{n}$ and $\hat{\sigma}=\sum_{i=1}^{n}\frac{(\ln x_i-\hat{\mu})^2}{n}$
WE	$f(x)=\frac{\beta}{\alpha}\left(\frac{x}{\alpha}\right)^{\beta-1}\exp\left[-\left(\frac{x}{\alpha}\right)^{\beta}\right]$	$\hat{\beta}=\left[\left(\sum_{i=1}^{n}x_i\hat{\beta}\ln x_i\right)\left(\sum_{i=1}^{n}x_i\hat{\beta}\right)^{-1}-n^{-1}\sum_{i=1}^{n}\ln x_i\right]^{-1}$ and $\hat{\alpha}=\left[\left(\frac{1}{n}\right)\sum_{i=1}^{n}x_i\hat{\beta}\right]^{1/\hat{\beta}}$
RY	$f(x)=\frac{x}{\sigma^2}\exp\left(-\frac{x^2}{2\sigma^2}\right)$	$\hat{\sigma}=\sqrt{\sum_{i=1}^{n}x_i/2n}$
EX	$f(x)=\frac{1}{\theta}\exp(-\frac{x}{\theta})$	$\hat{\theta}=\overline{x}$
GA	$f(x)=\frac{1}{\Gamma(\alpha)\beta^{\alpha}}x^{\alpha-1}\exp\left(-\frac{x}{\beta}\right)$	$\hat{\beta}=\frac{\overline{x}}{\alpha}$ and $\ln(\hat{\alpha})-\psi(\hat{\alpha})=\ln\left(\frac{1}{n}\sum_{i-1}^{n}x_i\right)-\frac{1}{n}\sum_{i=1}^{n}\ln x_i$
IGU	$f(x)=\left[\frac{\lambda}{2\pi x^3}\right]^{1/2}\exp\left\{-\frac{\lambda(x-\mu)^2}{2\mu^2 x}\right\}$	$\hat{\mu}=\overline{x}$ and $\hat{\lambda}=n\left[\sum_{i=1}^{n}x_i^{-1}-(\overline{x})^{-1}\right]^{-1}$
ER	$f(x)=\frac{1}{b(c-1)!}\left(\frac{x}{b}\right)^{c-1}\exp\left(-\frac{x}{b}\right)$	$\hat{b}=\frac{\overline{x}}{c}$ and $\ln(\hat{c})-\frac{d}{d\hat{c}}n\ln[(\hat{c}-1)!]=\ln\left(\frac{1}{n}\sum_{i-1}^{n}x_i\right)-\frac{1}{n}\sum_{i=1}^{n}\ln x_i$
BR	$f(x)=\frac{aqx^{a-1}}{b^a[1+(x/b)^a]^{1+q}}$	$\frac{n}{a}+\sum_{i=1}^{n}\ln(x_i/b)=(1+q)\sum_{i=1}^{n}\ln(x_i/b)\left[\left(\frac{b}{x_i}\right)^{a}+1\right]^{-1}$ and $n=(1+q)\sum_{i=1}^{n}\left[\left(\frac{b}{x_i}\right)^{a}+1\right]^{-1}$ and $\frac{n}{q}=\sum_{i=1}^{n}\ln\left[\left(\frac{x_i}{b}\right)^{a}+1\right]$
IGA	$f(x)=\frac{\beta^p}{\Gamma(p)}x^{-p-1}\exp\left(-\frac{\beta}{x}\right)$	$\frac{np}{\beta}=\sum_{i=1}^{n}\frac{1}{x_i}$ and $n\ln\beta-n\psi(p)=\ln\sum_{i=1}^{n}x_i$

scale parameter [32]. We density function can be written as

$$f(x)=\frac{\beta}{\alpha}\left(\frac{x}{\alpha}\right)^{\beta-1}\exp\left[-\left(\frac{x}{\alpha}\right)^{\beta}\right]\quad ,x>0,\quad \alpha>0,\quad \beta>0 \tag{9}$$

where β is shape parameter and $\alpha$is a parameter scale. By applying the transformation method in Eq. (5), wind power density can write as

$$\begin{aligned}f_P(p)&=f_X(h^{-1}(p))\left|\frac{d[h^{-1}(p)]}{dp}\right|\\&=\frac{\beta}{\alpha}\left[\frac{\left(\frac{p}{u}\right)^{1/3}}{\alpha}\right]^{\beta-1}\exp\left[-\left(\frac{\left(\frac{p}{u}\right)^{1/3}}{\alpha}\right)^{\beta}\right]\left|\frac{1}{3u^{1/3}p^{2/3}}\right|\\&=\frac{\beta}{3u^{1/3}p^{2/3}\alpha}\left[\frac{p}{u\alpha^3}\right]^{(\beta/3)-(1/3)-(2/3)}\left[\frac{p}{u\alpha^3}\right]^{2/3}\exp\left[-\left(\frac{p}{u\alpha^3}\right)^{\beta/3}\right]\end{aligned}$$

$$f_P(p)=\frac{\beta}{3u\alpha^3}\left[\frac{p}{u\alpha^3}\right]^{(\beta/3)-1}\exp\left[-\left(\frac{p}{u\alpha^3}\right)^{\beta/3}\right] \tag{10}$$

Let $\beta'=\beta/3$ and $\alpha'=u\alpha^3$, thus the distribution of wind power in Eq. (10) derived from Weibull wind speed density is also recognized as a Weibull with shape parameter β' and scale parameter α'. This identified distribution makes an analysis be relatively easy. Therefore, the mean value of power transported by the wind can be expressed as

$$\begin{aligned}E(P)&=\alpha'\Gamma\left(1+\frac{1}{\beta'}\right)\\&=\frac{A\rho}{2}\alpha^3\Gamma\left(1+\frac{3}{\beta}\right)\end{aligned} \tag{11}$$

On the other hand, the mean value of the for maximum power that can be extracted by a wind turbine can be written as

$$E(P_B)=\frac{8A\rho}{27}\alpha^3\Gamma\left(1+\frac{3}{\beta}\right) \tag{12}$$

and also, the mean value of airstream wind power with power coefficient C_p can be written as

$$E(P_{C_p})=\frac{A\rho C_p(\lambda,\beta)}{2}\alpha^3\Gamma\left(1+\frac{3}{\beta}\right) \tag{13}$$

Here, the air density was assumed to be $\rho=1.16\ \mathrm{kg/m^3}$ [17]. Villanueva and Feijoo [11] was assumed $C_p(\lambda,\beta)=0.45$, however, this value can be changes depending on wind turbine technology being used.

Table 2
The result of goodness of fit tests found based on Kolmogorov Smirnov test, Akaike's Information Criterion, Bayesian Information Criterion and the selected distribution (in **bold**) for each station.

Station	Goodness-of-fit method						Station	Goodness-of-fit method					
	KS	R^2 (%)	**AIC**	R^2 (%)	**BIC**	R^2 (%)		**KS**	R^2 (%)	**AIC**	R^2 (%)	**BIC**	R^2 (%)
1	**GA**	99.70	GA	99.70	GA	99.70	**35**	**ER**	99.38	WE	99.24	WE	99.24
2	**BR**	99.52	GA	98.98	GA	98.98	**36**	**BR**	99.54	BR	99.54	BR	99.54
3	**BR**	99.60	GA	99.57	GA	99.57	**37**	**IGA**	99.72	IGA	99.72	IGA	99.72
4	**BR**	99.34	GA	99.20	GA	99.20	**38**	**GA**	96.97	WE	97.32	WE	97.32
5	**IGA**	98.00	IGA	98.00	IGA	98.00	**39**	**GA**	99.59	GA	99.59	GA	99.59
6	**WE**	99.34	GA	99.30	GA	99.30	**40**	**GA**	99.84	WE	99.72	WE	99.72
7	**GA**	98.75	GA	98.75	GA	98.75	**41**	**IGA**	99.61	IGA	99.61	IGA	99.61
8	**WE**	97.87	RY	98.07	WE	97.87	**42**	WE	99.92	**BR**	99.94	BR	99.94
9	**BR**	99.34	GA	98.91	GA	98.91	**43**	**IGA**	99.42	GA	99.38	GA	99.38
10	**GA**	99.79	GA	99.79	GA	99.79	**44**	BR	99.67	**GA**	99.71	GA	99.71
11	**GA**	99.76	GA	99.76	GA	99.76	**45**	BR	99.46	**GA**	98.85	GA	98.85
12	**BR**	99.21	GA	99.09	GA	99.09	**46**	**BR**	99.25	BR	99.25	BR	99.25
13	**GA**	98.74	GA	98.74	GA	98.74	**47**	**GA**	99.53	GA	99.53	GA	99.53
14	**GA**	99.73	GA	99.73	GA	99.73	**48**	**IGA**	99.61	IGA	99.61	IGA	99.61
15	**GA**	99.18	GA	99.18	GA	99.18	**49**	**BR**	98.44	GA	98.33	GA	98.33
16	**BR**	98.69	GA	98.31	GA	98.31	**50**	**GA**	99.30	GA	99.30	GA	99.30
17	**GA**	99.63	GA	99.63	GA	99.63	**51**	**GA**	98.66	GA	98.66	GA	98.66
18	**GA**	99.70	GA	99.70	GA	99.70	**52**	WE	93.89	**GA**	94.93	GA	94.93
19	**GA**	99.86	GA	99.86	GA	99.86	**53**	WE	96.58	**GA**	97.16	GA	97.16
20	BR	98.12	**IGA**	98.52	IGA	98.52	**54**	**ER**	97.24	GA	92.46	GA	92.46
21	**WE**	97.79	GA	97.70	GA	97.70	**55**	**BR**	98.33	WE	97.82	WE	97.82
22	**GA**	99.16	GA	99.16	GA	99.16	**56**	**RY**	87.55	WE	73.11	WE	73.11
23	WE	99.09	**GA**	99.90	GA	99.90	**57**	**ER**	98.99	GA	96.37	GA	96.37
24	**BR**	98.77	GA	98.66	GA	98.66	**58**	**RY**	96.67	GA	96.04	GA	96.04
25	**WE**	99.86	WE	99.86	WE	99.86	**59**	**ER**	96.26	GA	92.90	GA	92.90
26	WE	99.53	**BR**	99.54	WE	99.53	**60**	**GA**	96.97	GA	96.97	GA	96.97
27	**GA**	99.29	GA	99.29	GA	99.29	**61**	**GA**	99.08	GA	99.08	GA	99.08
28	**BR**	98.36	GA	98.10	GA	98.10	**62**	**GA**	98.28	GA	98.28	GA	98.28
29	**GA**	98.94	GA	98.94	GA	98.94	**63**	**GA**	98.11	GA	98.11	GA	98.11
30	**ER**	99.66	WE	99.65	WE	99.65	**64**	**GA**	98.98	GA	98.98	GA	98.98
31	**GA**	99.65	GA	99.65	GA	99.65	**65**	**GA**	98.31	GA	98.31	GA	98.31
32	**GA**	99.62	GA	99.62	GA	99.62	**66**	**GA**	99.48	GA	99.48	GA	99.48
33	**BR**	99.43	BR	99.43	BR	99.43	**67**	**GA**	97.13	GA	97.13	GA	97.13
34	**ER**	99.09	GA	99.01	GA	99.01	**–**	**–**	–	–	–	–	

6.1.2. Wind power density derived from gamma(GA) and Erlang (ER)

Among earlier statistical studies of wind speed involving probabilities distribution beginning 60 years ago were performed using GA. It was found that generalized gamma distribution is adequate to describe the surface of wind speed distribution almost everywhere in Europe [35]. Until now, GA also has been applied to modeling the wind speed data, [10]. GA can be view as a generalization of the exponential distribution with mean $1/\lambda$. GA can also formed Erlang and Chi-square distribution for some specific value of parameter [32]. The probability density function for GA is

$$f(x)=\frac{1}{\Gamma(\alpha)\beta^{\alpha}}x^{\alpha-1}\exp\left(-\frac{x}{\beta}\right)\quad ,x>0,\alpha>0,\beta>0 \tag{14}$$

By using transformation method in Eq. (5), wind power distribution can write as

$$f_P(p)=\frac{1}{3\Gamma(\alpha)\alpha^{\beta}u^{\alpha/3}}(p)^{(\alpha/3)-1}\exp\left[-\frac{p^{1/3}}{u^{1/3}\beta}\right] \tag{15}$$

This form of distribution is difficult to match with any theoretical statistical distribution. Thus, it is difficult to obtain the mean value of wind power. However, either analytically approach or Monte Carlo simulation is usually being used to handle with this kind of problem. Despite that, since the wind power PDF is a function of wind speed PDF, the problem of finding the mean of wind power distribution can easily be solved by using the information of raw moment of wind speed pdf. The k-th raw moment for GA is

$$E(X^k)=\frac{\beta^k\Gamma(\alpha+k)}{\Gamma(\alpha)} \tag{16}$$

for reference, see [36]. Based on Eq. (2), the mean value for power transported by the wind can be expressed as

$$E(P)=\frac{A\rho\beta^3\Gamma(\alpha+3)}{2\Gamma(\alpha)} \tag{17}$$

While, the mean value of the maximum power that can be extracted by a wind turbine in Eq. (2) can be written as

$$E(P_B)=\frac{8A\rho\beta^3\Gamma(\alpha+3)}{27\Gamma(\alpha)} \tag{18}$$

On the other hand, by using mean 3th raw moment of GA, the mean value of wind power with power coefficient C_p in Eq. (3) can be written as

$$E(P_{C_p})=\frac{A\rho C_p(\lambda,\beta)\beta^3\Gamma(\alpha+3)}{2\Gamma(\alpha)} \tag{19}$$

6.1.3. Wind power density derived from burr (BR)

BR is also known as a Singh–Maddala distribution. This distribution was among the most commonly used as a model for distribution of personal income. Another distribution such as paralogistic distribution and log-logistic distribution is a particular case of BR for some specific value of the parameter [37]. Recently, BR has been applied to wind speed data and also shows

Table 3
Theoretical mean of wind power per unit area for each station derived from Eq. (2).

Station	Latitude	Longitude	Theoretical mean power (W/m^2)	Station	Latitude	Longitude	Theoretical mean power (W/m^2)
1	N01°28.225	E103°53.637	6.059	**35**	N04°15.016	E117°56.166	4.879
2	N04°16.260	E103°25.826	7.549	**36**	N06°08.218	E100°20.880	5.703
3	N05°23.470	E100°23.213	8.196	**37**	N04°12.038	E100°39.841	4.323
4	N01°33.734	E110°23.329	4.584	**38**	N05°19.980	E115°14.315	6.849
5	N03°15.702	E101°39.103	1.658	**39**	N02°12.789	E102°14.055	5.437
6	N02°15.510	E102°10.364	4.173	**40**	N02°03.715	E102°35.587	6.054
7	N03°58.238	E102°20.863	1.384	**41**	N03°41.267	E101°31.466	2.937
8	N04°37.781	E101°06.964	7.935	**42**	N04°33.155	E101°04.856	3.873
9	N05°23.890	E100°24.194	5.343	**43**	N02°43.418	E101°58.105	4.089
10	N02°49.246	E101°48.877	7.152	**44**	N03°19.592	E101°15.532	7.340
11	N03°00.620	E101°24.484	3.388	**45**	N05°20.313	E116°09.769	2.576
12	N03°49.138	E103°17.817	8.543	**46**	N05°51.865	E118°05.479	6.772
13	N03°57.726	E103°22.955	12.178	**47**	N01°29.068	E103°41.064	3.596
14	N03°06.612	E101°42.274	1.471	**48**	N02°55.915	E101°40.909	8.563
15	N05°37.886	E100°28.189	4.224	**49**	N03°06.376	E101°43.072	2.505
16	N01°29.815	E103°43.617	1.618	**50**	N02°00.875	E112°55.640	1.262
17	N04°53.940	E100°40.782	2.669	**51**	N02° 27.000	E103° 50.000	23.279
18	N06°09.520	E102°17.262	3.665	**52**	N06° 10.000	E102° 17.000	17.069
19	N06°09.520	E102°15.059	5.210	**53**	N04° 28.000	E101° 22.000	11.108
20	N02°59.645	E101°44.417	1.187	**54**	N03° 47.000	E103° 13.000	5.863
21	N04°35.880	E103°26.096	5.811	**55**	N05° 23.000	E103° 06.000	6.795
22	N03°06.287	E101°33.368	5.596	**56**	N06° 29.000	E100° 16.000	0.689
23	N02°18.856	E111°49.906	2.075	**57**	N06° 12.000	E100° 24.000	7.056
24	N03°10.587	E113°02.433	4.706	**58**	N04° 34.000	E101° 06.000	1.972
25	N04°25.456	E114°00.731	9.323	**59**	N05° 18.000	E100° 16.000	15.999
26	N02°07.992	E111°31.351	2.526	**60**	N02° 16.000	E102° 15.000	20.149
27	N05°53.623	E116°02.596	4.447	**61**	N03°07.000	E113°01.000	7.051
28	N04°45.529	E115°00.813	2.571	**62**	N05°56.000	E116°03.000	10.359
29	N06°19.903	E099°51.517	5.579	**63**	N01°29.000	E110°20.000	9.036
30	N06°25.424	E100°11.046	14.052	**64**	N06°55.000	E116°50.000	24.110
31	N05°18.455	E103°07.213	3.827	**65**	N06°20.000	E099°44.000	11.569
32	N01°27.308	E110°29.498	1.440	**66**	N05°54.000	E118°04.000	15.266
33	N01°14.425	E111°27.629	0.938	**67**	N04°18.000	E118°07.000	7.853
34	N05°21.528	E100°17.864	3.022	**–**	–	–	

Table 4
Mean square error for each fitted semivariogram model on mean value of the power transported by the wind, $E(p)$.

Semivariogram model	**MSE (Peninsular Malaysia)**	**Semivariogram model**	**MSE (East Malaysia)**
Exponential	743.66	Exponential	1031.38
Gaussian	243.63	Gaussian	488.50
Linear	**102.61**	**Linear**	**284.26**
Logarithmic	253.18	**Logarithmic**	**289.63**
Power	**114.52**	**Power**	**296.54**
Quadratic	797.81	Quadratic	761.48
Rational quadratic	201.59	Rational quadratic	612.42
Spherical	719.92	Spherical	1433.07
Wave	**111.46**	**Wave**	**318.01**

a good result [35,38]. The probability density function for BR is

$$f(x)=\frac{aqx^{a-1}}{b^{a-1}[1+(x/b)^{a}]^{1+q}},\quad a>0, b>0, q>0 \tag{20}$$

Parameter a and q are shape parameter, while b is scale parameter. Applying the transformation method, wind power distribution can write as

$$f_P(p)=\frac{aq(p/u)^{(a/3)-1}}{3b^{a-1}u[1+(p/ub^3)^{a/3}]^{1+q}} \tag{21}$$

This form of distribution is also difficult to match with any available statistical distribution. Therefore, the derivation for the mean of wind power pdf is also is also follow the same procedure as in Gamma case. The information of kth raw moment of a BR is

$$E(X^k)=\frac{b^k\Gamma(1/(k/\alpha))\Gamma(q-(k/\alpha))}{\Gamma(q)},\quad -a<k<qa \tag{22}$$

for reference, see [36]. The mean value of power transported by the wind can be expressed as

$$E(P)=\frac{A\rho b^3\Gamma(1+(1+3/\alpha))\Gamma(q-(3/a))}{2\Gamma(q)} \tag{23}$$

The same procedure also can be applied to obtain the mean value for the maximum power that can be extracted by a wind turbine and also the mean value of wind power with power coefficient

Wind power density derived from inverse gamma (IGA)

IGA belongs to the family of Pearson distribution. This distribution is reciprocal of a Gamma random variable. It also has been applied in the analysis involving wind speed data (for example, see [15]). Probability density function for IGA is

$$f(x)=\frac{\beta^p}{\Gamma(p)}x^{-p-1}\exp\left(-\frac{\beta}{x}\right)\quad ,p>0,\beta>0 \tag{24}$$

Wind power distribution derived from IGA wind speed probability distribution can be written as

$$f_P(p)=\frac{\beta^p}{3\Gamma(p)u^{-(p/3)}}[p]^{-(p/3)-1}\exp\left[-\frac{\beta u^{1/3}}{p^{1/3}}\right] \tag{25}$$

This form of distribution is also difficult to identify with any theoretical statistical distribution. Therefore, the derivation of mean will be based on raw of moment for Inverse Gamma

distribution. The kth raw moment of IGA is

$$E(X^k) = \frac{\beta^k \Gamma(p-k)}{\Gamma(p)} \tag{26}$$

for reference, see [36]. The mean value of the for power transported by the wind can be written as

$$E(P) = \frac{A\rho\beta^3}{2(p-1)(p-2)(p-3)} \tag{27}$$

However, the Eq. (26) indicate that the parameter p need to be larger than 3. If $p<3$, the mean value will become negative. This indicates that the higher moments for IGA are not exist. This limitation makes Eq. (27) can only be used in a certain condition. Thus, in this study, we take a more general approach for estimating the mean of wind power derived from IGA wind speed distribution. Monte Carlo integration is a good method to handling with this kind of problem. Let $g(X)=\frac{1}{2}\rho X^3$ be a function of interest, where X is a random variable with IGA density function. Then, the mathematical expectation of random variable $Y=g(X)$ can be computed as

$$E[g(X)] = \int_0^\infty g(x)f(x)dx$$

Since n random variable can be generate from the distribution of X, thus, the unbiased estimator of $E[g(X)]$ is the sample mean $E[g(X)] = \sum_{i=1}^{n} g(X_i)/n$. In fact, by the Strong Law of Large Numbers, $E[g(X)]$ will converges to $\sum_{i=1}^{n} g(X_i)/n$ with probability 1, for detail see [39].

By applying the formulas derived above, the theoretical mean of wind power is computed for each station as shows in Table 3. However, since our data in term of km/h, the constant 0.0214 should be include to the formulas before the computing is done.

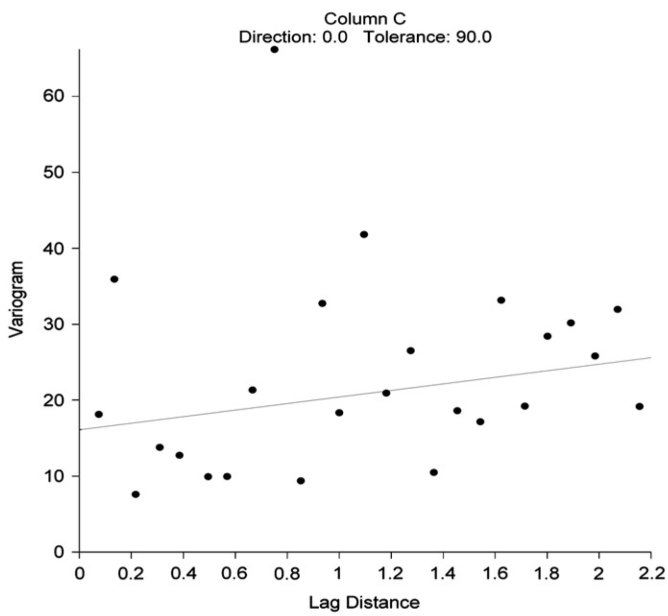

Fig. 2. The fitted linear semivariogram model for mean power in Peninsular Malaysia.

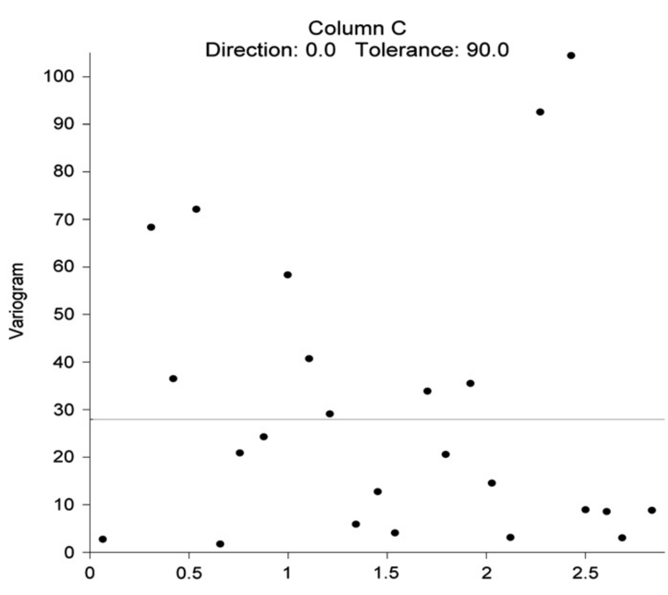

Fig. 3. The fitted linear semivariogram model for mean power in East Malaysia.

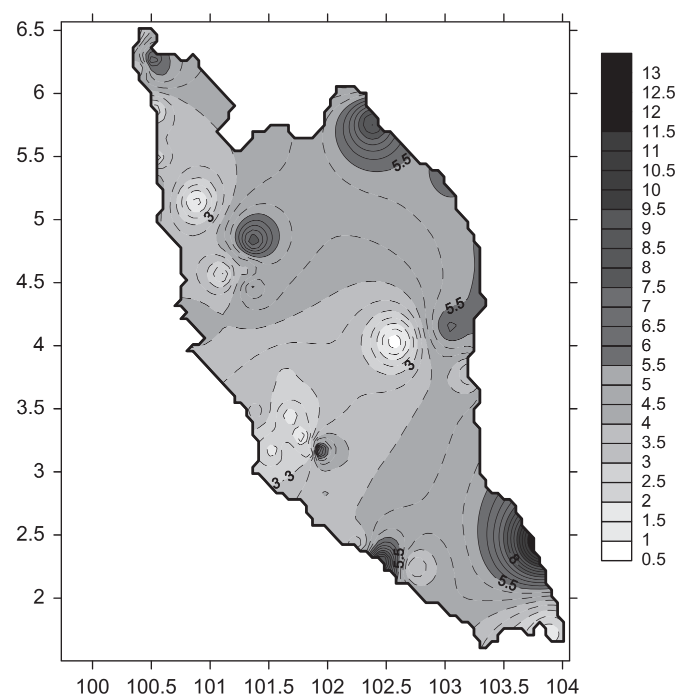

Fig. 4. Map of theoretical mean power in Peninsular Malaysia.

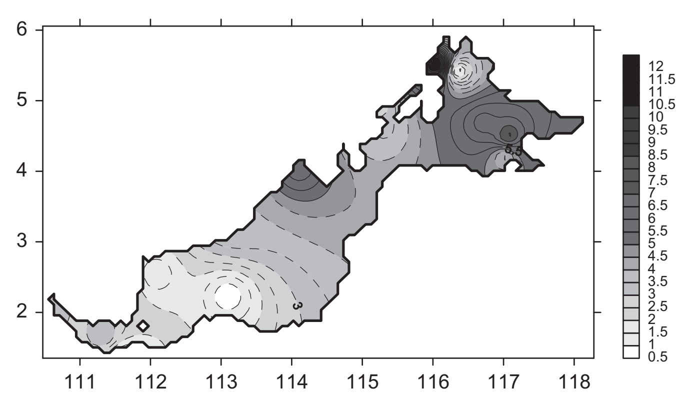

Fig. 5. Map of theoretical mean power in East Malaysia.

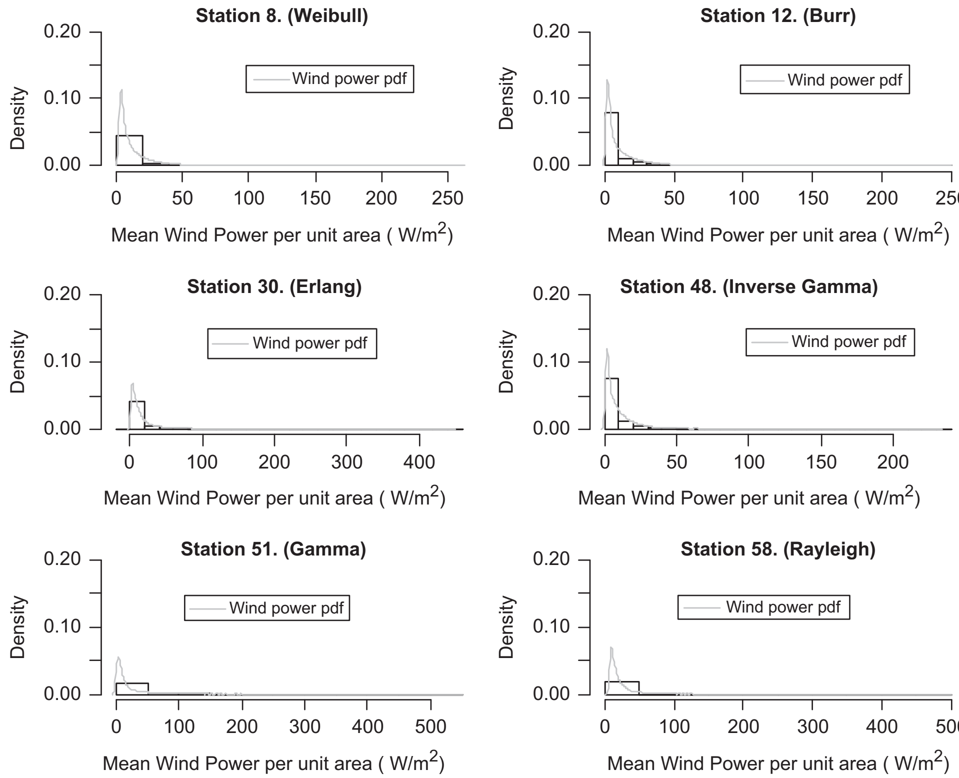

Fig. 6. Experimental histograms for wind power and its respective density function.

6.2. Semivariogram

Before determining the spatial estimate of wind speeds, an assessment is made on the semivariogram in order to investigate the spatial correlation of the data. In this study, the suitability of proposed semivariogram model has been determined using the mean square error (MSE). The mean square error defined as

$$MSE(\gamma(\mathbf{h})) = E\left[(\gamma(\mathbf{h}) - \hat{\gamma}(\mathbf{h}))^2\right] = \frac{\sum_i^{N(\mathbf{h})} (\gamma_i(\mathbf{h}) - \hat{\gamma}_i(\mathbf{h}))^2}{N(\mathbf{h})} \tag{28}$$

Although MSE for fitted model may indicate a minimum value, it does not necessarily imply that the fitted model will have similar form as the theoretical model. Thus, in study we use our subjective assessment to select the best semivariogram model. The fitted semivariogram with relatively small MSE and found to satisfy the particular form of semivariogram will be chosen as the best fitted model. Here, we know that Eq. (2)–(4) only differ in term of some constant. Thus, the spatial correlation of wind power data produce by Eq. (2) will also be same as spatial correlation for wind power data produce by Eq. (3) and (4). Hence, in order to investigate the spatial correlation of wind power in Malaysia, only data produce by Eq. (4) will be consider. Table 3 shows the value of MSE for each fitted semivariogram model for the mean value of the power transported by the wind; P, produce by Eq. (2).

From Table 4, it is found that Linear, Power and Wave semivariogram have relatively small value of MSE. Based on subjective assessment after making a comparison for each fitted model with the theoretical semivariogram shape, linear model has been chosen as the best semivariogram model for the theoretical mean of wind speed in Peninsular Malaysia and also for East Malaysia. Fig. 2 shows a fitted linear semivariogram with estimated nugget and scale effect of 3.07 and 7.85, respectively; implying that the peninsula wind

Table A1
List of semivariogram models.

Model	Variogram
Exponential	$\gamma(h) = \begin{cases} \tau^2 + \sigma^2(1-\exp(-h)) & \text{if } h>0 \\ 0 & \text{otherwise} \end{cases}$
Gaussian	$\gamma(h) = \begin{cases} \tau^2 + \sigma^2(1-\exp(-h)) & \text{if } h>0 \\ 0 & \text{otherwise} \end{cases}$
Linear	$\gamma(h) = \begin{cases} \tau^2 + \sigma^2 h & \text{if } h>0 \\ 0 & \text{otherwise} \end{cases}$
Logarithmic	$\gamma(h) = \begin{cases} \tau^2 + \sigma^2[\log_e(h)] & \text{if } h>0 \\ 0 & \text{otherwise} \end{cases}$
Power	$\gamma(h) = \begin{cases} \tau^2 + \sigma^2 \lfloor h^n \rfloor & \text{if } h>0 \\ 0 & \text{otherwise} \end{cases}$ Where $0<n<2$
Quadratic	$\gamma(h) = \begin{cases} \tau^2 + \sigma^2(2h-h^2) & \text{if } h>0 \\ \sigma^2 & \text{if } h\geq 1 \end{cases}$
Rational Quadratic	$\gamma(h) = \begin{cases} \tau^2 + \sigma^2\left[\frac{h^2}{1+h^2}\right] & \text{if } h>0 \\ 0 & \text{otherwise} \end{cases}$
Spherical	$\gamma(h) = \begin{cases} \tau^2 + \sigma^2[1.5h-0.5h^3] & \text{if } h<1 \\ \sigma^2 & \text{if } h\geq 1 \end{cases}$
Wave	$\gamma(h) = \begin{cases} \tau^2 + \sigma^2\left(1-\frac{\sin(h)}{h}\right) & \text{if } h>0 \\ 0 & \text{otherwise} \end{cases}$

Where τ^2 is nugget effect, σ^2 is scale of structured component of variogram and h is separation distance, for detail see [31,40,41].

Table B1
The parameter estimates for Lognormal, Weibull Rayleigh, Exponent, Gamma and Inverse Gaussian by maximum likelihood method.

Station	Parameter estimates									
	Lognormal		Weibull		Rayleigh	Exponential	Gamma		Inverse Gaussian	
	μ	σ	α	β	Θ	Θ	α	β	μ	λ
1	1.565	0.460	6.611	1.723	4.863	5.871	2.589	2.268	5.871	3.720
2	1.360	0.419	5.395	1.557	4.066	4.798	2.555	1.880	4.798	3.138
3	1.771	0.302	7.647	2.027	5.391	6.755	3.756	1.799	6.755	4.966
4	1.415	0.567	5.902	1.582	4.463	5.282	2.162	2.445	5.281	3.060
5	0.865	0.477	3.377	1.490	2.650	3.205	2.232	1.355	3.025	1.909
6	1.330	0.565	5.612	1.526	4.174	4.879	2.117	2.304	4.789	2.833
7	1.049	0.457	3.991	1.656	2.982	3.545	2.465	1.439	3.545	2.280
8	1.779	0.442	7.933	2.036	5.546	6.930	3.357	2.066	6.931	3.481
9	1.487	0.432	6.124	1.634	4.666	5.444	2.565	2.119	5.444	3.560
10	1.695	0.370	7.308	1.847	5.336	6.462	3.086	2.092	6.463	4.469
11	1.491	0.329	5.843	2.002	4.090	5.162	3.495	1.477	5.161	3.713
12	1.664	0.374	7.126	1.802	5.200	6.302	2.984	2.112	6.302	4.351
13	1.895	0.338	8.848	1.929	6.316	7.807	3.279	2.381	7.807	5.606
14	1.170	0.371	4.316	1.882	3.087	3.816	3.111	1.227	3.816	2.638
15	1.448	0.439	5.874	1.676	4.371	5.217	2.601	2.004	3.508	2.154
16	1.016	0.508	3.905	1.546	2.994	3.508	2.241	1.565	3.491	2.142
17	1.383	0.346	5.311	1.886	3.811	4.691	3.235	1.451	4.691	3.330
18	1.506	0.340	5.960	1.980	4.225	5.265	3.373	1.560	5.264	3.756
19	1.472	0.504	6.124	1.619	4.609	5.461	2.368	2.307	5.461	3.315
20	1.046	0.414	3.938	1.628	2.967	3.497	2.577	1.357	3.497	2.342
21	1.328	0.773	5.774	1.350	4.652	5.283	1.632	3.236	5.283	2.574
22	1.347	0.646	5.711	1.362	4.673	5.197	1.808	2.875	5.197	2.797
23	1.374	0.281	5.089	2.106	3.559	4.497	4.021	1.119	4.497	3.389
24	1.288	0.708	5.455	1.378	4.379	4.967	1.737	2.857	4.966	2.544
25	1.602	0.524	6.926	1.750	5.060	6.165	2.460	2.506	6.165	3.656
26	1.351	0.441	5.236	1.895	3.748	4.644	2.869	1.618	1.351	0.441
27	1.572	0.336	6.366	1.954	4.526	5.622	3.388	1.658	5.622	4.022
28	1.150	0.646	4.660	1.466	3.628	4.206	1.899	2.215	4.206	2.285
29	1.449	0.553	6.094	1.553	4.655	5.457	2.169	2.519	5.457	3.195
30	1.698	0.651	8.135	1.513	6.187	7.185	2	3.636	7.186	3.803
31	1.482	0.381	5.916	1.874	4.250	5.232	3.055	1.712	5.232	3.583
32	1.152	0.374	4.260	1.837	3.078	3.767	3.027	1.245	3.767	2.611
33	1.078	0.276	3.798	2.053	2.670	3.353	3.946	1.066	3.353	2.551
34	1.464	0.353	5.776	1.883	4.145	5.102	3	1.605	5.102	3.599
35	1.522	0.431	6.193	1.895	4.434	5.490	3	1.883	5.490	3.549
36	1.586	0.468	6.714	1.781	4.887	5.962	2.663	2.237	3.962	3.727
37	1.336	0.394	5.218	1.637	3.931	4.631	2.694	1.099	4.631	3.144
38	1.360	0.780	5.944	1.386	4.714	5.421	1.662	3.262	5.421	2.625
39	1.687	0.283	6.998	2.088	4.902	6.174	3.906	1.580	6.174	4.661
40	1.581	0.460	6.675	1.795	4.848	5.924	2.682	2.207	5.924	3.745
41	1.321	0.328	4.976	1.866	3.582	4.392	3.299	1.079	4.392	3.174
42	1.598	0.316	6.399	2.210	4.440	5.663	3.835	1.477	5.663	4.114
43	1.440	0.384	5.746	1.738	4.226	5.086	2.843	1.789	5.086	3.492
44	1.649	0.451	7.124	1.755	5.215	6.326	2.708	2.336	6.326	4.008
45	1.354	0.350	5.199	1.784	3.795	4.596	3.082	1.490	4.596	3.252
46	1.787	0.270	7.667	2.213	5.315	6.767	4.161	1.063	6.767	5.171
47	1.385	0.460	5.537	1.714	4.079	4.917	2.559	1.923	4.917	3.139
48	1.372	0.452	5.549	1.512	4.332	4.960	2.336	2.122	4.960	3.188
49	1.148	0.534	4.524	1.514	3.498	4.055	2.137	1.897	4.055	2.433
50	1.099	0.375	4.054	1.776	2.962	3.589	2.961	1.212	3.589	2.483
51	2.208	0.255	11.59	2.193	8.005	10.143	4.376	2.339	10.237	7.885
52	2.005	0.362	9.872	1.946	6.660	7.846	3.260	2.677	8.729	6.057
53	1.796	0.423	8.226	1.746	5.843	6.838	2.764	2.640	7.296	4.788
54	1.603	0.505	7.024	1.593	5.021	5.591	2	2.717	6.267	3.835
55	1.802	0.334	7.993	1.933	5.629	6.891	3.145	0.483	7.064	5.051
56	1.486	0.365	5.844	2.101	3.492	3.763	3.350	1.543	5.170	3.603
57	1.648	0.499	7.361	1.554	5.466	6.177	2	2.890	6.577	4.042
58	1.702	0.340	7.246	1.929	4.957	5.892	3.379	1.897	6.408	4.552
59	1.818	0.547	8.763	1.613	6.189	6.926	2.239	3.496	7.827	4.596
60	1.813	0.473	8.522	1.690	6.121	7.129	3	3.021	7.577	4.760
61	1.715	0.356	7.368	1.935	5.185	6.354	3.301	1.974	6.516	4.573
62	1.949	0.230	8.900	2.076	6.224	7.831	4.588	1.714	7.865	6.220
63	1.686	0.359	7.247	1.781	5.253	6.315	3.061	2.094	6.412	4.482
64	2.004	0.476	10.345	1.673	7.664	9.146	2.474	3.720	9.021	5.778
65	1.815	0.414	8.372	1.780	6.022	7.224	2.802	2.648	12.006	2.434
66	1.986	0.336	9.608	1.958	6.799	8.422	3.419	2.483	8.490	6.057
67	1.658	0.436	7.236	1.695	5.245	6.149	2.629	2.444	6.424	4.183

power is random. While for East Malaysia, the fitted linear semivariogram with estimated nugget and scale effect of 7.16 and 0.337, respectively is shown in Fig. 3. Based on Figs. 2 and 3, the results found that the linear semivariogram also cannot adequately fit the data. This implies that there is a lack of spatial correlation of wind speed in Peninsular Malaysia region. The presence of nugget effect for fitted linear semivariogram indicates the roughness of a data. Based on the properties of semivariogram discussing here, we can conclude there is no clear pattern on how the wind power at a particular location is influenced by the wind power at a neighboring location. However, we suggest that a more comprehensive analysis need to be conducted in the future, involving more stations to get a better understanding about semivariogram of the data as well as the spatial correlation of wind speed in Peninsular Malaysia.

In order to create a map that representing the spatial trend of a wind power in Malaysia, geostatistical technique was used in this study. Inverse distance weighting method is one of the simplest methods that can be used for the estimation of a wind power in some point of a spatial field, starting from the values sample from other points of the same field. Fig. 4 shows the interpolation maps of wind power in Peninsular Malaysia. The overview of maps indicates that the wind power in Peninsular Malaysia is low. However, it is clearly shows that the northeast, northwest and southeast regions in Peninsular Malaysia are identified to having a higher wind power potential compared to other regions. Thus, here we suggest that these regions should be explored in more detail in further in order to locate a specific area that has a good wind regime and a large tendency to develop wind energy.

On the other hand, Fig. 5 shows the interpolation maps of wind power in East Malaysia. The southern region of Sabah state was found to have the highest wind power as compared to the other regions. Thus, southern region is found as a best region to be further investigated for wind energy technology development. Based on Figs. 4 and 5, the variability of wind power either in peninsular or in East Malaysia indicate some randomness. In addition, for better illustration, we provide some experimental histograms for wind power and its respective density function for particular stations derived from different wind speed pdf as shown in Fig. 6.

7. Conclusion

In this study, the features of wind power density based on the dependency of the suitable wind speed distribution have been obtained analytically using transformation technique. Since the wind power density has been obtained, the mean power density which is referred as an important indices related to the estimation of potential wind energy have been obtained by using the concept of raw moment and Monte Carlo approach. Next, the analysis involving mean power density has been carried out by using semivariogram and inverse distance weighting method in order to draw some conclusion about variability of wind power in Malaysia. An analysis of semivariogram indicates the lack of spatial correlation of wind power in Malaysia. The map of the mean power density over Malaysia indicates that the northeast, northwest and southeast region

Table B2
Result of parameter estimates for Burr and Inverse Gamma distribution by maximum likelihood method.

Station	Parameter estimates					Station	Parameter estimates				
	Burr			Inverse Gamma			Burr			Inverse Gamma	
	q	*a*	*b*	*p*	*β*		*q*	*a*	*b*	*p*	*β*
1	11.357	1.809	24.397	2.145	7.976	**35**	99.73	1.906	69.03	2.115	7.504
2	1.608	2.265	5.283	2.464	7.732	**36**	16.86	1.844	30.31	1.998	7.444
3	2.136	2.667	8.798	3.120	15.491	**37**	0.917	2.813	3.585	2.780	8.738
4	152.89	1.589	139.60	1.833	5.608	**38**	0.797	2.624	2.019	1.409	3.697
5	0.797	2.624	2.019	2.427	4.633	**39**	2.823	2.545	9.403	3.548	16.54
6	20.321	1.568	37.40	1.879	5.323	**40**	74.32	1.808	71.86	2.070	7.752
7	3.878	1.913	7.282	2.443	5.648	**41**	1.349	2.732	4.406	3.175	10.07
8	0.797	2.624	2.019	1.075	3.742	**42**	16.73	2.294	21.42	2.880	11.84
9	1.660	2.249	6.130	2.455	8.738	**43**	1.533	2.400	5.461	2.793	9.753
10	2.912	2.246	10.39	2.677	11.96	**44**	4.397	2.016	13.59	2.070	8.295
11	4.041	2.308	9.831	2.942	10.92	**45**	1.365	2.631	4.613	3.013	9.800
12	2.283	2.272	8.752	2.735	11.89	**46**	6.355	2.415	15.671	3.629	18.76
13	7.026	2.081	21.40	3.078	17.25	**47**	46.86	1.734	50.439	2.227	6.988
14	3.878	1.913	7.282	2.653	6.999	**48**	0.762	2.813	3.300	2.500	7.969
15	2.365	1.764	7.434	2.335	7.895	**49**	5.409	1.671	11.386	2.084	5.073
16	3.890	1.764	7.434	2.214	4.717	**50**	2.887	2.186	5.795	2.784	6.912
17	1.660	2.249	6.130	2.930	9.759	**51**	2.823	2.545	9.403	3.669	28.931
18	4.041	2.308	9.831	2.903	10.90	**52**	7.026	2.081	21.400	2.604	15.778
19	4.505	1.837	12.63	1.980	6.564	**53**	20.32	1.568	37.404	2.331	11.161
20	0.873	2.720	2.581	2.727	6.387	**54**	4.397	2.016	13.594	2.081	7.978
21	218.43	1.354	307.9	1.451	3.735	**55**	6.356	2.423	15.669	2.904	14.668
22	223.31	1.366	298.5	1.719	4.810	**56**	5.892	2.059	13.125	2.602	9.374
23	2.283	2.272	8.752	3.413	11.56	**57**	6.355	2.415	15.671	2.140	8.650
24	135.11	1.384	188.2	1.557	3.963	**58**	4.397	2.016	13.594	2.833	12.895
25	213.32	1.763	1.462	1.832	6.839	**59**	7.026	2.081	21.400	1.857	8.536
26	286.75	1.899	102.8	2.106	6.299	**60**	7.132	2.111	20.899	2.130	10.140
27	2.283	2.272	8.752	2.931	11.78	**61**	6.305	2.309	15.601	2.718	12.427
28	161.08	1.471	146.81	1.692	3.868	**62**	7.146	2.285	21.404	4.264	26.524
29	164.33	1.559	160.05	1.900	6.038	**63**	4.227	2.011	13.24	2.845	12.755
30	20.321	1.568	37.404	1.526	5.804	**64**	2.682	2.324	9.102	2.154	12.443
31	5.892	2.059	13.12	2.581	9.249	**65**	20.424	1.668	37.423	2.434	12.006
32	3.739	2.133	7.154	2.756	7.196	**66**	7.146	2.285	21.404	2.868	17.375
33	2.495	2.630	4.751	3.692	9.419	**67**	6.241	2.316	15.382	2.358	9.864
34	3.356	2.211	8.965	2.880	10.36						

of Peninsular Malaysia are found to have the potential to be further explored for the purpose of generating wind energy. On the other hand, for East Malaysia, the southern region of Sabah is found as the best region to be further investigated in the future for wind energy development. A more comprehensive analysis need to be conducted in the future, with more stations to get a better map of wind power potential in Malaysia.

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Appendix A

See Table A1 here.

Appendix B

See Tables B1 and B2 here.

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